Investigating Multiple Model Techniques for Target Tracking

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Abstract

In this paper, we investigate the fundamental assumptions of popular target tracking algorithms. These assumptions rarely hold in the real world and can have significant effects on current tracking systems. These analyses provide motivation for new algorithms that overcome the difficulties in current algorithms, providing better target tracking systems.

1.0 INTRODUCTION

The wide scope of target tracking applications include satellite surveillance systems, ocean/battlefield surveillance, ballistic missile systems and even nonmilitary applications such as air traffic control (ATC) where estimation and prediction of target trajectories can be used to determine safety margins between aircraft.

Any solution for the general tracking problem consists of two main tasks, estimation and association. Estimation uses noisy measurements coming from a single target and provides an estimate for the current state and prediction for future states. Combining the estimation capabilities with measurements from multiple targets is the data association problem. Although estimation and association problems must be integrated to form a viable solution in the real world, it is not uncommon to see work focused on one of these two technologies with subsequent integration into a complete tracking system. This paper focuses on the estimation problem and analyzes the techniques that are currently employed in the state-of-the-art estimators for tracking systems.

Today, estimators are often implemented using multiple-model techniques that automatically switch between appropriate models, in order to adapt to a target that is, in general, more complicated than any one model. Perhaps the most successful of the multiple model techniques is the Interacting Multiple Model (IMM) an algorithm that has proven to be an excellent compromise between high performance and reasonable computation requirements.

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14. ABSTRACT
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Although we focus our analysis on the popular IMM tracker that has superior performance over its less-sophisticated precursors, such as General Pseudo Baysian (GPB1) and (GPB2) methods, the fundamental theoretical concerns introduced here can cause problems in all of the above multiple-model techniques. Before focusing on these problems we provide some background to help the reader better understand the complications that can arise. We start by tracking a simple target whose model is known and observe how problems arise as the complexity of the problem increases.

2.0 SINGLE MODEL

Consider an ideal target tracking scenario in a stochastic environment where a target model and a series of measurements are available. The state estimate at time k given knowledge of the measurement at time k is denoted as x(k|k). The measurement at the next time step is given as z(k+1). We assume the model is linear, markov, and known. By 'markov' we mean that knowledge of the system state before the previous timestep adds no new information in determining the optimal estimate. With this assumption, only the previous timestep's estimate must be propagated to the next timestep's computation to ensure optimality, because the previous timesteps estimate fully includes all information given by prior measurements. By ‘known’ we mean that the model is correct and the noise statistics fully specified. We also assume that the noise characteristics of both the input signal and the measurement are Gaussian.

When these conditions are met, a Kalman Filter (using Bayes rule to combine the measurements and the model predictions) obtains a current estimate, x(k+1|k+1), that is optimal (See Figure 1).

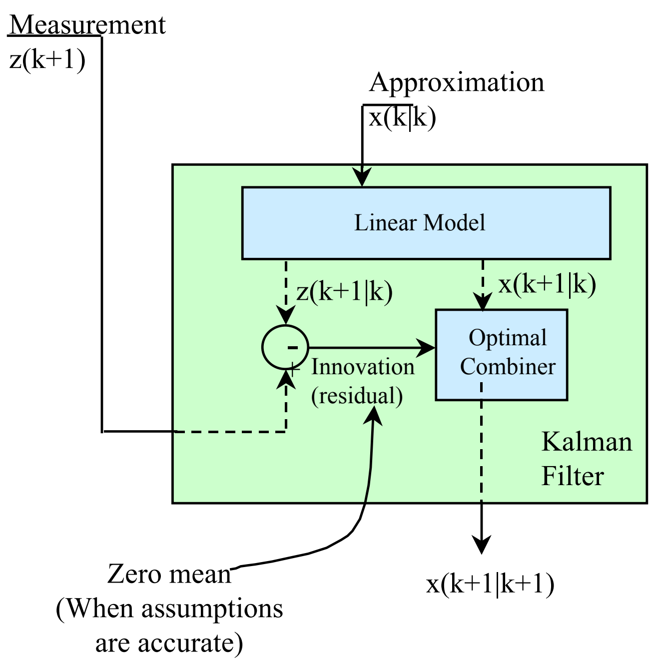

Figure 1 Optimal combination of measurement and model prediction.

To assure optimality, as the target behavior becomes more complex the model complexity must follow suit. In the case where the model can not be found or is too costly to run, a simplified model can be substituted. At this point, the known model assumption no longer valid.

Input and process noise can be increased to account for the lack of model fidelity in those parts of the model that are deterministic. In this case, the model predictions, x(k+1|k), are discounted and the influence of the raw measurement, z(k+1), is increased. In the extreme, the model would be ignored and the estimate would be based solely on the measurement. To solve this lack of confidence in the single model, multiple models are frequently used as described below (See Figure 2).

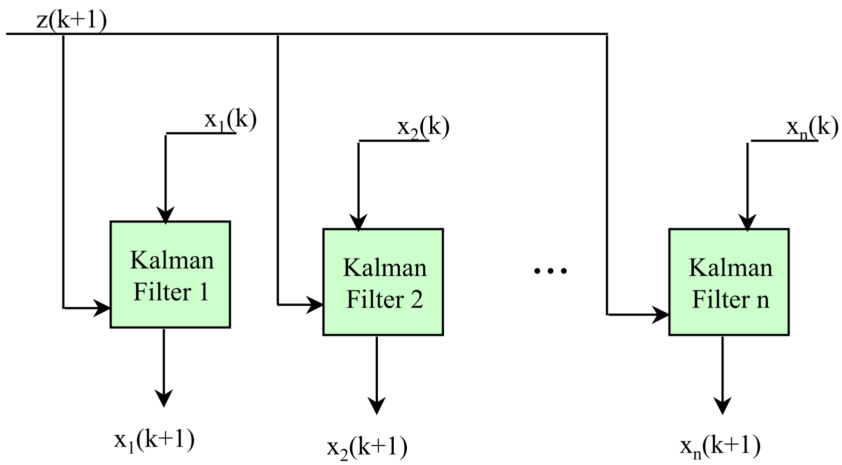

Figure 2 Multiple Models working independently.

3.0 MULTIPLE MODELS

If a set of models is known to include an accurate model of the targets behavior, a non-switching multiple model technique is appropriate. Each model in the set works on its own estimates without mixing them with other models. A model probability is computed and used to weight the model's influence in a combination with other models to form an overall system estimate. Though this situation may have little practical value, it is a valuable theoretical problem upon which more likely scenarios, can be built and studied.

To enable a set of multiple models to track a target that is more complex than any of the given models, we allow for model switching. Any one model from the set is not sophisticated enough to describe the target's behavior but at any given timestep the target behaves according to one of the set's finite number of models. The model that describes the target at two subsequent timesteps may or may not be the same.

Even in the rare case where one of the finite number of models accurately predicts a targets behavior, the other models in the set are incorrect. Nevertheless, the filter performs computations under the assumption that it contains an accurate model. When a Kalman filter contains the wrong model, errors build and can ruin the tracking algorithm.

For example, consider three models describing a left turn, straight flight, and a right turn (See Figure 3). If the target is flying straight (according to the straight flight model) the right turn model constantly predicts behavior that carries the plane to the right of the targets true position. Assuming the measurement noise is reasonable (small), the difference between the measurement z(k+1) and the models prediction $z_r(k+1|k)$ will cause the innovation to have a non-zero mean or bias (See Figure 1). The bias propagates leading to not only poor prediction from the faulty model, in this case the right turn model, but also to the overall system approximation.

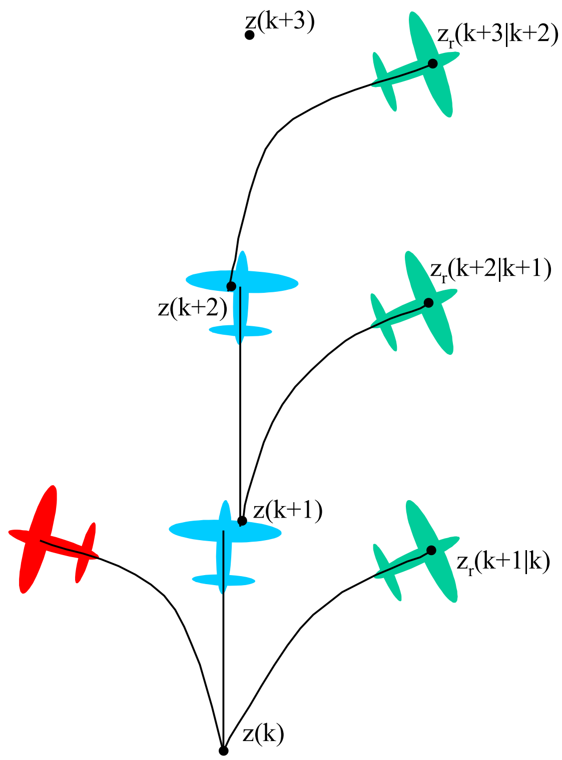

Figure 3 Example of innovation bias in right turn model when target is in straight flight.

In the real-world, even less knowledge of the target is available. Frequently, however, model characteristics can be delimited allowing one to make reasonable choices for the model set. With a constant velocity model, knowledge of the minimum and maximum target velocities can be used to develop several models that represent extremes of the target's characteristics as well as models that lie in between the extremes. With enough models, one model is likely to behave close to the target's behavior (during any given timestep) so that model mismatch is minimized.

This approach of choosing one of many simple models to predict the behavior of a more complex target is frequently quite effective in the real world as evidenced by the popularity and success of IMM target tracking algorithms. The theoretical assumptions that go in to developing the IMM, however, is that one of the available models will match the target's behavior at any given time. Since the target moves about the behavior space in a continuous manner, however, the probability is low that any of the models match the target. Furthermore, the more models included in the set from which an algorithm can choose, the slower the algorithm becomes and the more likely models will compete against themselves, lowering performance.

4.0 CURRENT MULTIPLE-MODEL TECHNIQUES

From the previous section we see that the majority of multiple model techniques have a dilemma. When using too few models, the inevitable model mismatch with the target will force estimates to ignore the model due to high uncertainty. Using too many models, however, leads to lower performance due to competing models. Unfortunately, finding a proper balance may not be possible in some applications.

The effects of innovation bias, briefly discussed earlier, do occur in the popular Interactive Multiple Model (IMM), violations are not accounted for and can cause anomalous behavior under certain conditions. In the multiple-model techniques the model mismatch can easily cause a bias in the residual's mean to be significant.

5.0 SIMULATIONS

To illustrate the theoretical problems inherent in typical multiple model trackers we describe two simulations using the IMM algorithm. Both simulations have three constant velocity models given as 10, 0, -10 m/s^2. The structure of the three models and the truth model are constructed from a constant position model with a velocity bias, where the model input supplies the bias (that is, when there is no input, the velocity is zero). In the Kalman Filter framework, Q and R for the truth model, the three models, and the measurement are 0.1. In the first simulation the true target velocity is –3 1/3, making the distance to the second closest model twice as far as the distance to the closest model. Figure 4, plots the difference between the true target position and the estimate for each of the models, denoted as Xm1, Xm2, and Xm3. Figure 4 also shows the IMM estimator indicated by the symbol * which at each timestep coincides with the estimate from one of the three models, indicating that the multiple model system puts all its weight on the closest of the two models, ignoring the other two models. Because the solid line, which denotes the difference between the true target sequence and the measurement sequence, is smaller than the estimation error, the predictions could be improved by simply using the measurement in place of the IMM estimates.

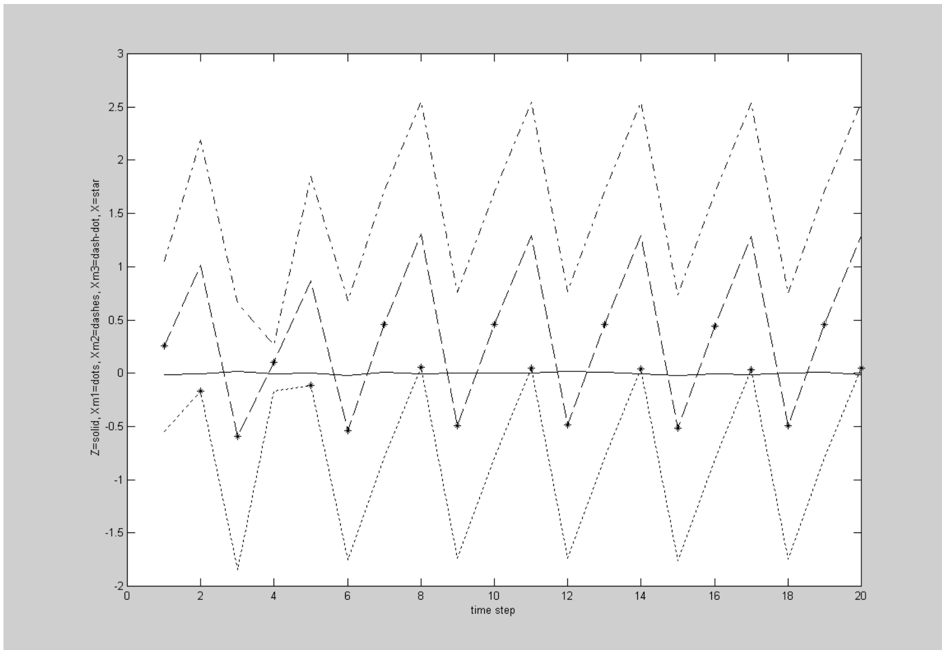

Figure 4 In this case the measurement sequence is a better estimate than the IMM algorithm (see text for details).

The second simulation is identical to the first except the truth model has a bias of 9 m/s^2. The estimated position puts all the weight on the nearest model as opposed to balancing between the two nearest.

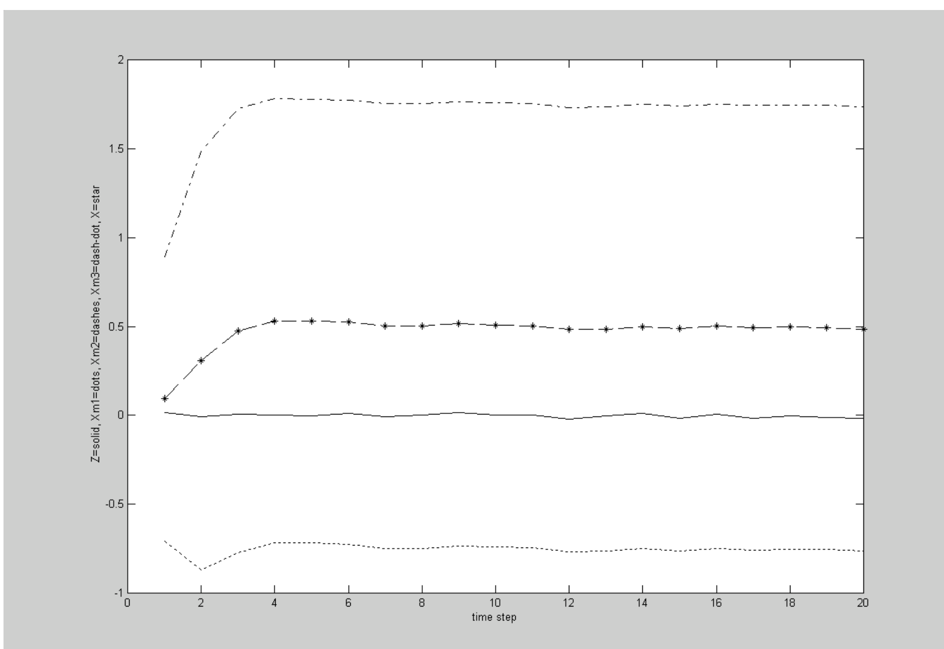

Figure 5 The truth model is very near one model, but measurements are still better estimates.

In both simulations the measurements, though noisy, provide a much better estimate than does the multiple model estimator.

6.0 CONCLUSION

Although estimation theory has a long history and is well researched, multiple-model algorithms, such as IMM for tracking applications, that rely on estimation theory, have amble room for performance improvements and creative research. This research is focusing on ways to intelligently combine multiple models to form a more accurate state estimate. Because tracking has multiple and diverse applications, research effort in this area promises to yield a high payoff. This paper is intended to motivate, "A Continuum of Models for Stochastic Estimation", a companion paper also presented at this conference.